The Design, Implementation and Evaluation of the CenceMe Application

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Outline

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- Main contributions
- Design and implementation
- Evaluation and Results
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- Future Work

Introduction – CenceMe

- Mobile application which infers people's sensing presence with the use of sensor enabled mobile phones.
- Software developed on: Nokia N95.
- Sharing of information through social networks (e.g. Facebook, MySpace).

Motivation and Problem Definition

- The people's need for communication with other people.
- Importance of sensing information ("where are you?", "what u doing?")
- Ability of mobile phones to provide sensor networks

⟶ new application domain where people: carriers of sensing devices, sources and consumers of sensed events.

Main contributions

- Design, implementation and evaluation of fully functional mobile sensor application
- Classifiers' design on mobile phones
- RAM, CPU and energy measurements
- Evaluate the CenceMe application through a user study

Mobile Phones' Limitations (1)

- OS, API and Operational:
  - N95 uses Symbian operating system and JME
  - use small amounts of memory and computational resources
  - limited programmability
  - not able to fully deploy an application
  - manufacturers maintain devices and operational networks' closed nature.
- Security:
  - signed keys – protection from attacks

Mobile Phones' Limitations (2)

- Energy management:
  - waste of battery power: GPS, Bluetooth, GPRS radios and data upload
  - Symbian and JME do not provide duty cycle

  ⟶ design sensing duty cycle with less frequently sensor sampling.

Design Issues (1)

- Split-Level Classification:
  - sensing presence is derived from classifiers
  - classify sensor data by pushing some classification to the phone and some to the servers
  - phone output: primitives stored in a database to be retrieved for more complex classification
  - backend output: facts stored in a database to be retrieved and published
  - advantages: support customized tags, provides resiliency to cellular/WiFi dropouts, minimizes the sensor data sent, reduces the energy consumed, increase the user's privacy and integrity

Design Issues (2)

- Duty-Cycle:
  - How long can the sleep interval be? The larger the sleep interval the lower the classification responsiveness
  - Idea: minimizes sampling but maintains the application's responsiveness thus operating as near to real time as possible

  ⟶ lower duty cycle but increasing sensing rate when a buddy's page is accessed. This leads to bandwidth and storage improvements.

- Portability:
  - the majority of mobile phones use java virtual machine to support JME ⟶ push more to JME

Design and Implementation of CenceMe

- Software running on Nokia N95 and backend infrastructure
- **Operations**: sensing, raw sensed data classification, people's presence presentation, primitives' upload
- **Primitives result**: sound samples, accelerometer data, scanned Bluetooth MAC addresses, GPS readings, random photos

Software Architecture (1)

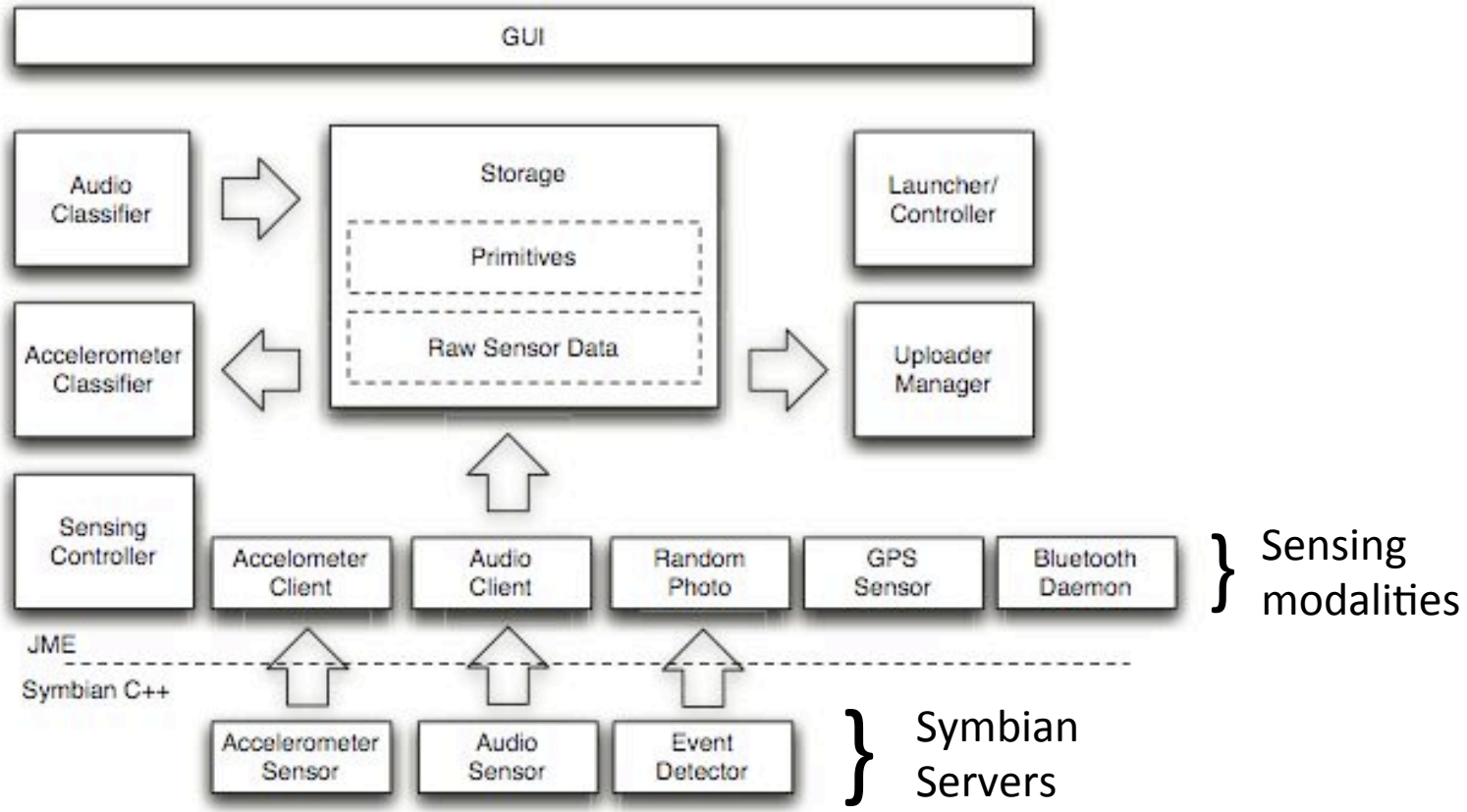


Figure 1: Architecture of the CenceMe phone software.

Software Architecture (2)

- **ClickStatus**: visualizes sensing presence
- **WatchTasks:** restarts the processes that fail
- **Each component is a single thread**: if one fails does not affect the rest

Backend Software (1)

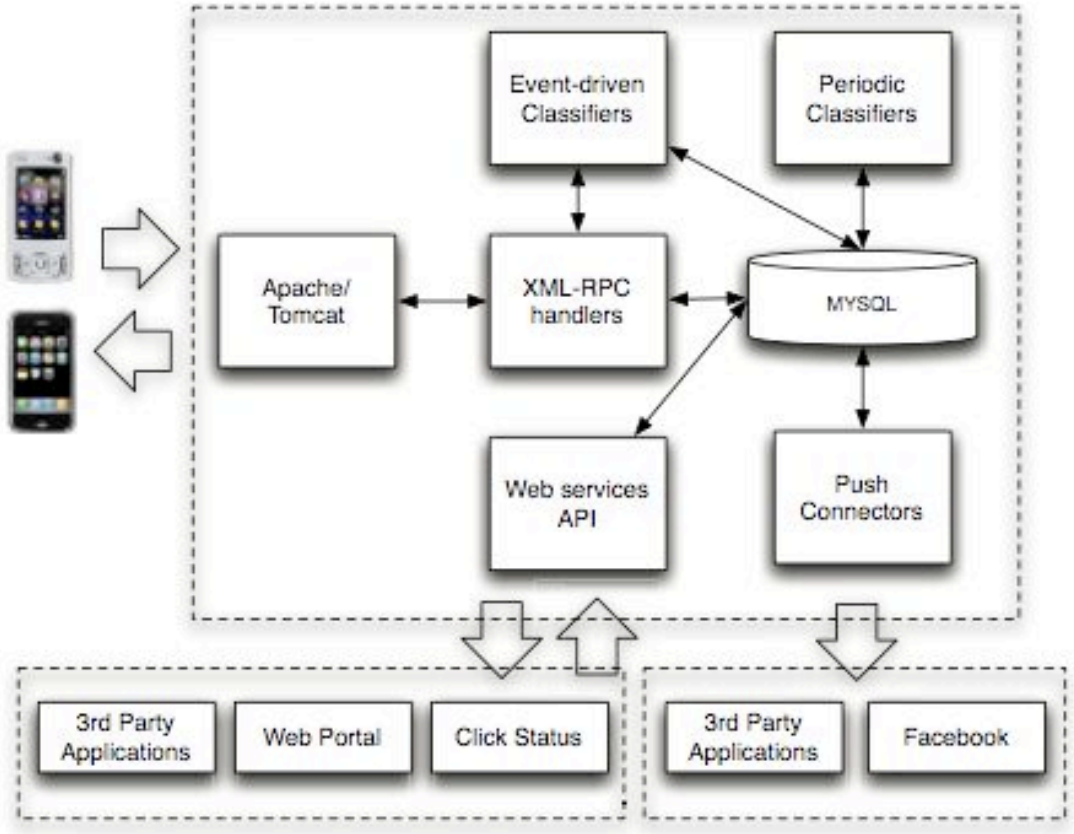


Figure 3: Software architecture of the CenceMe backend.

Backend Software (2)

- **Phone ⟷ Backend Communication**: data exchange whenever the phone has primitives to upload
- **Presence representation and publishing**: set of icons to represent presence with “push” or “pull” approach

CenceMe Classifiers – Phone Classifiers

- **Audio**: outputs the audio primitive which indicates if the sample is human voice. Two steps:
  - feature extraction: discrete Fourier transform (human voice: 250Hz – 600Hz)
  - classification: machine learning algorithm – training set consists of audio sample of human voice and environmental conditions
- **Activity**: takes accelerometer data and outputs the current activity. Two components:
  - preprocessor: takes the data and extracts features. Calculates the mean and deviation
  - classifier itself

Activity Classifier Results

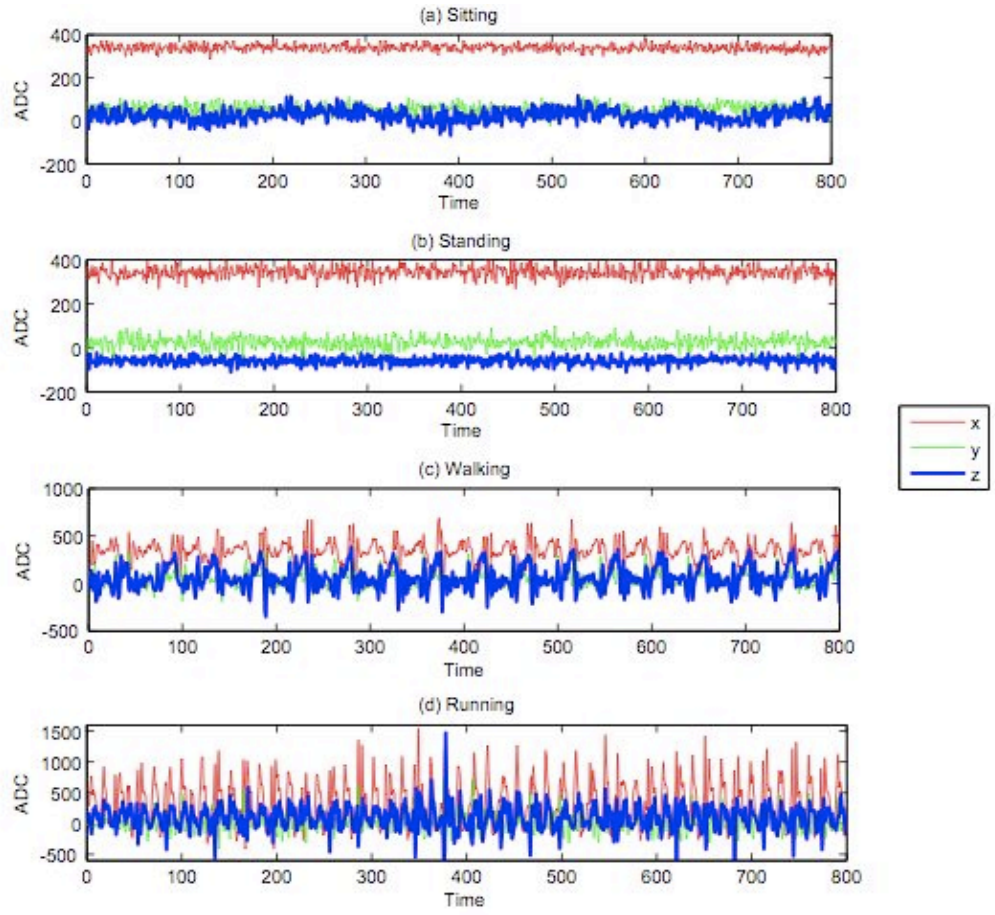


Figure 6: Accelerometer data collected by the N95 on board accelerometer when the person carrying the phone performs different activities: sitting, standing, walking, and running.

- x, y, z axes: accelerometer readings

CenceMe Classifiers – Backend Classifiers (1)

- Two ways:
  - event triggered: input the primitives and outputs the current activity
  - periodic: run periodically based on the availability of data in a window of time
- **Conversation**: indicates whether a person is in a conversation. Input: audio primitives but are not accurate ⟶ rolling window of N phone audio primitives (N = 5).
  - If 2 out of 5 indicate voice ⟶ "conversation" state
  - If 4 out of 5 indicate no voice ⟶ "no conversation" state

CenceMe Classifiers – Backend Classifiers (2)

- **Social Context:** uses primitives and facts to output the social context:
  - neighborhood conditions: indicates whether there any CenceMe buddies close to the user (Bluetooth MAC Address)
  - social status: uses the activity and conversation classifiers' output to show if a person is with other CenceMe buddies talking, alone, or at a party. Also defines if partying or dancing with an approach that combines sound volume and activity.

CenceMe Classifiers – Backend Classifiers (3)

- **Mobility Mode Detector:** takes as input the GPS estimates. It distinguishes if travelling in a vehicle or not (using speed measurements). Uses JRIP algorithm.
- **Location:** location estimates used by other classifiers, using GPS samples
- **Am I Hot:** uses metrics (nerdy, party animal, healthy, greeny). Users compare themselves with others

Evaluation and Results

- 8 users
- 1 week period at intervals of about 15 to 30 minutes
- Data collected at different locations carrying the mobile phone in different positions on the body and environmental conditions

General Results

- **Activity Classifier:**

Table 1: Activity classifier confusion matrix

	Sitting	*Standing*	*Walking*	*Running*
Sitting	0.6818	0.2818	0.0364	0.0000
Standing	0.2096	0.7844	0.0060	0.0000
Walking	0.0025	0.0455	0.9444	0.0076
Running	0.0084	0.0700	0.1765	0.7451

- uses accelerometer on N95
- **difficulty distinguishing** sitting from standing given the similarity in the raw accelerometer traces

General Results (2)

- **Conversation Classifier**

Table 2: Conversation classifier confusion matrix

	Conversation	*Non-Conversation*
Conversation	0.8382	0.1618
Non-Conversation	0.3678	0.6322

- High accuracy but high rate of false positives due to a combination of classifier design and mis-annotation by participants
- Reports conversation even if the person is not talking – someone is talking nearby
- The classifier remains in the conversation state for longer time than real conversation (quickly enters a “conversation state”, moves slower out of that state)

Impact of Phone Placement on the Body

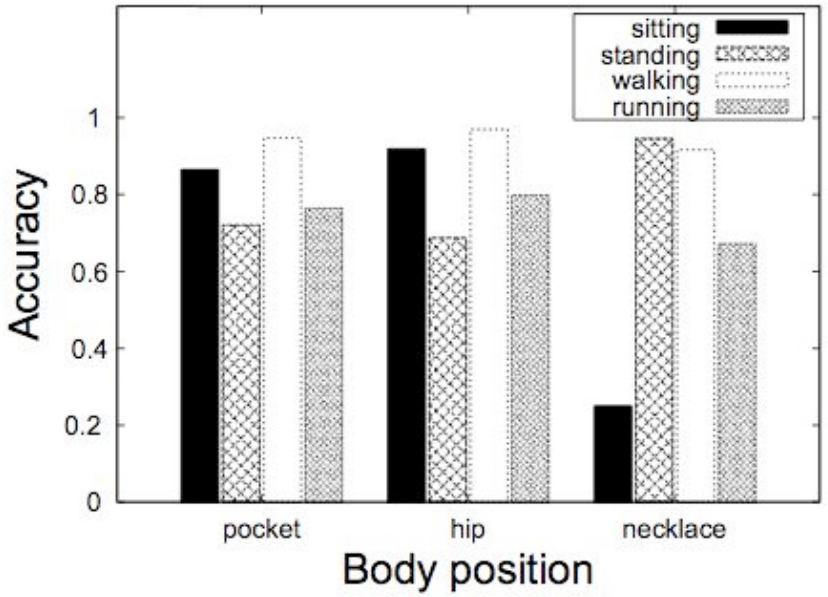
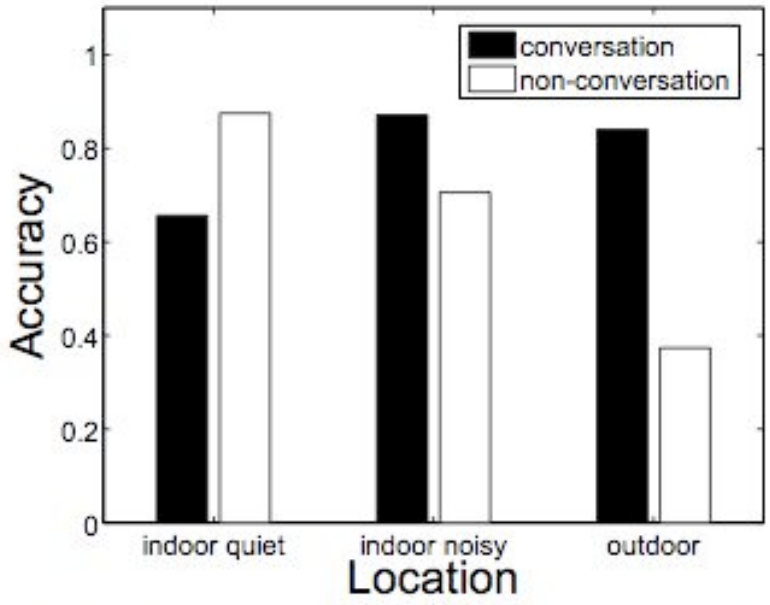


Figure 7: Activity classification vs. body position.

- x axis: body position, y axis: accuracy
- Body placement affects the activity inference accuracy
- Different places: pocket, lanyard (length and type affect results), clipped to a belt
- Pocket and belt produce similar results
- Lanyard produces poor accuracy while sitting and relatively accuracy while running
- Lanyard: 88% and 72% accuracy for conversation and no conversation while in pocket: 82% for conversation and 71% for no conversation ➡ accuracy is less sensitive

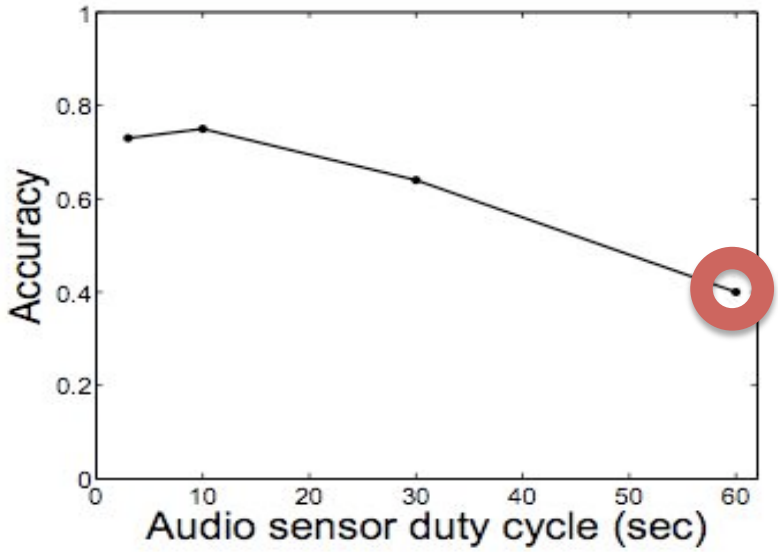
Impact of Environment



(a) Conversation classifier in different locations.

- x axis: location, y axis: accuracy
- Activity classification accuracy is independent of the environment
- Conversation classification accuracy is affected by the environment conditions
- Indoor noisy: 85% success
- Outdoor: increase in false positives but high accuracy
- Indoor quiet: lower accuracy because of the background noise

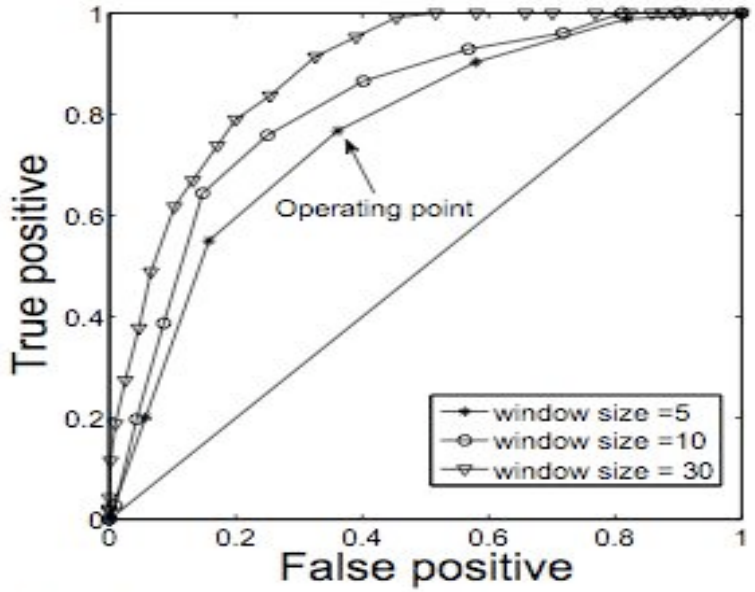
Impact of Duty Cycle (1)



(b) Conversation classifier accuracy with a variable duty cycle.

- x axis: duty cycle, y axis: accuracy
- Little advantage having a sleeping time < 10s but longer duty cycle
- 40% accuracy with the conversation classification for 60s duty cycle
- **Longer duty cycle** ⟶ reduction of the conversation classifier rolling window size which means higher misclassification rate

Impact of Duty Cycle (2)



(c) ROC curves for the conversation classifier.

- x axis: false positive, y axis: true positive
- The larger the window the larger the true positives to false positives ratio
- N=5: delay is 1.5 minutes (operating point)
- If N is increased the accuracy is increased but more delay

Power Benchmarks (1)

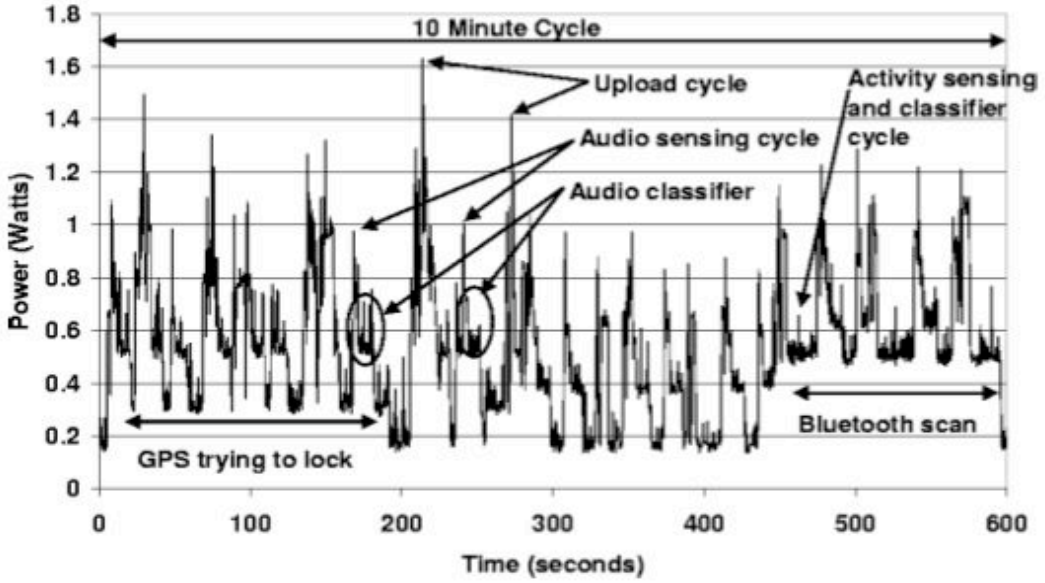


Figure 9: Details of the power consumption during a sampling/upload interval.

- x axis: time, y axis: power
- Highest spikes: upload of data
- Next highest spikes: audio sampling
- Accelerometer sampling and activity classification: fast and little use power

Power Benchmarks (2)

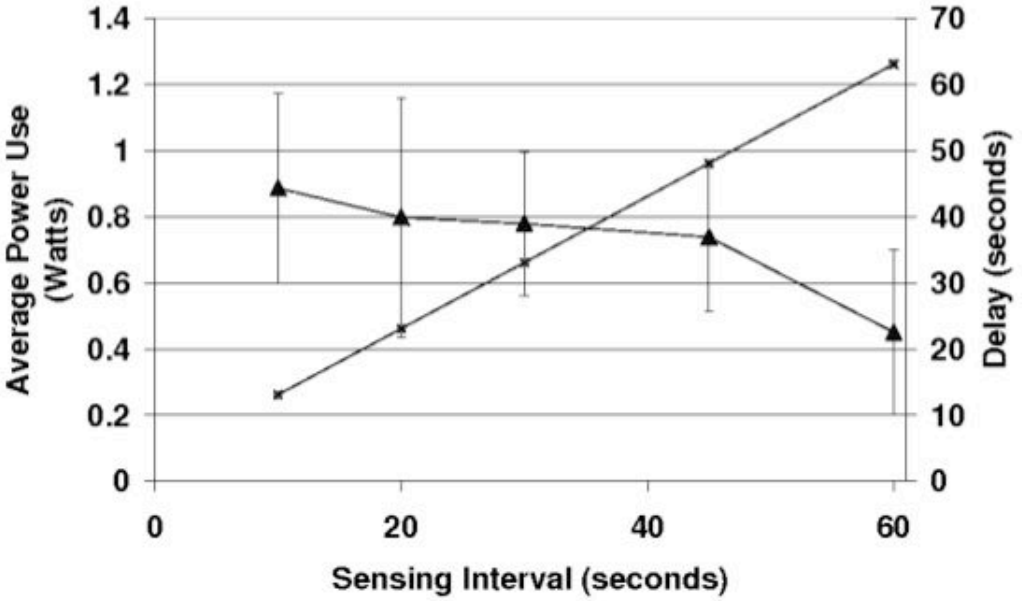


Figure 10: The tradeoff between energy consumption and data latency in CenceMe.

- x axis: seconds of sensing interval, y axis: average power, second vertical axis: delay
- Combination of two lines: tradeoff between energy and data latency
- There is no optimal sampling interval because users requirements vary at different times
- Audio sampling and processing use a relatively high amount of energy

Memory and CPU Benchmarks

Table 4: RAM and CPU usage

	CPU	*RAM (MB)*
Phone idle	2% (+/- 0.5%)	34.08
Accel. and activity classif.	33% (+/- 3%)	34.18
Audio sampling and classif.	60% (+/- 5%)	34.59
Activity, audio, Bluetooth	60% (+/- 5%)	36.10
CenceMe	60% (+/- 5%)	36.90
CenceMe and ClickStatus	60% (+/- 5%)	39.56

- Audio sampling and feature vector extraction require more computation

User Study

- Tested with 22 people
- Nokia N95 with CenceMe
- 3 weeks
- Overall: location information is used the most, positive experience, some of the users liked the random pictures' feature and some disabled it

Related Work

- iCAMS, Twitter and WatchMe: CenceMe provides rich context about a person
- Inter Mobile Sensor Platform: CenceMe operates on less capable devices while remaining effective
- Previous works on activity inference and modeling using sensors: CenceMe implements the activity inference algorithms on commercial mobile phones

Future Work

- Less energy consumption: achieve 48 hour duration of battery life
- Improve privacy policy and ClickStatus interface, thus more powerful ways to browse their friends
- Minimize time for primitives and facts. It is required by the users to have real time access

Conclusion

- Sensing information is important to people to be able to communicate with other people, using sensor networks through mobile phones
- Implementation of an always-on application has many limitations and trade-offs
- **Contribution**: design a fully functional mobile sensor application
- **Strengths**: area with a growing interest
- **Weakness:** limited number of people who tested the application, not all results are accurate

Thank you